# Booms, Busts, and Fraud

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### Abstract

We examine firm managers' incentives to commit fraud in a model where firms seek funding from investors and investors can monitor firms at a cost in order to get more precise information about firm prospects. We show that fraud incentives are highest when business conditions are good, but not too good: in exceptionally good times, even weaker firms can get funded without committing fraud, and in bad times investors are more vigilant and it is harder to commit fraud successfully. As investors' monitoring costs decrease, the region in which fraud occurs shifts towards better business conditions. It follows that if business conditions are sufficiently strong, a decrease in monitoring costs actually increases the prevalence of fraud. If investors can only observe current business conditions with noise, then the incidence of fraud will be highest when investors begin with positive expectations that are disappointed ex post. Finally, increased disclosure requirements can exacerbate fraud. Our results shed light on the incidence of fraud across the business cycle and across different sectors.



JEL codes: E320, G300, G380.

Key Words: Boom, Credit Cycle, Fraud, Monitoring.

# 1 Introduction

*"It's only when the tide goes out that you can see who's swimming naked."*

*Warren Buffett*

Booms and busts are a common feature of market economies. Almost as common is the belief that a boom encourages and conceals financial fraud and misrepresentation by firms, which are then revealed by the ensuing bust. Examples in the last century include the 1920s (Galbraith, 1955), the "go-go" market of the 1960s and early 1970s (Labaton, 2002, Schilit, 2002), and the use of junk bonds and LBOs in the 1980s (Kaplan and Stein, 1993). Most recently, the long boom of the 1990s has been followed, first by recession, then by revelations of financial chicanery at many of America's largest companies.

Some argue that fraud in booms is exacerbated by inadequate rules and regulations. In the 1930s, this view led to the establishment of the SEC and numerous regulations on financial institutions; in the early 1990s, to anti-takeover legislation; and in the crisis just past, to the Sarbanes-Oxley Act. Yet others have argued that the root cause for the fraud lies in investors' overly optimistic expectations, which make fraudulently positive reports seem more plausible. For example, the Economist (2002) suggests:

> The remedy is disclosure, honest accounting, non-executive directors empowered to do their job — and, as always, skeptical shareholders looking out for their own interests. Without doubt, the last of these is most important of all. Alas, it is beyond the reach of regulators and legislators. ... The most important lesson of this bust, like every bust, is: buyer beware.

In this paper, we examine these arguments in a simple model of financing and investment. Firms require external funding. Rational investors may either rely on public but noisy signals of firms' prospects or else investigate these prospects more carefully. A firm with poor prospects may commit fraud, which makes the noisy public signal look more attractive but does not fool investors who investigate more carefully. Fraud is most likely to occur if times are relatively good and investors are relatively optimistic about the average firm's prospects.

Fraud is less likely in exceptionally good times, however, since investors are rationally willing to fund a firm even if its public signal is relatively unattractive. Fraud is also less likely in bad times, when investors are cautious about investing and so are less easily fooled.

Investors' expectations about the average firm's prospects change over time. In a dynamic setting, the incidence of fraud is highest when the business cycle has turned down but investors are not yet aware of this. Thinking conditions are still reasonably good, investors fund firms that "look good," and firms with poor prospects commit fraud so as to obtain funding. These very acts of fraud obscure the extent of the downturn. Eventually, reality intrudes, the downturn is revealed, and the incidence of fraud is much greater than anyone anticipated. Yet investors and firms have acted rationally; good times are most likely to lead to widespread fraud when the good times are ending, but the end of good times can only be known ex post. Indeed, it is when a number of firms that had been doing well are seen to be doing badly that investors know that the good times have ended. To reverse Buffett, it's only when you see a lot of people swimming naked that you know that the tide has gone out.

Thus, a model with rational behavior can reproduce many features of the boom-bust-fraud pattern. Although we do not claim that investors are always perfectly rational, the fact that rationality does not rule out this pattern suggests limits to the "buyer beware" school of policy response. Furthermore, our model suggests that measures aimed at improving disclosure per se can be counterproductive. To see why this is the case, however, we must first present our model in more detail.

In our model, managers need funding for their firms. Firms can be good or bad (i.e., investing in them can be positive or negative NPV), but due to private control benefits, managers want to get funding regardless. Investors observe a noisy free signal of the firm's true type, after which they can decide whether or not to monitor the firm more closely. Monitoring is costly, but reveals the firm's true type. Managers with bad projects can commit fraud, which increases the chance that the noisy free signal will be high even though the firm is truly bad. Committing fraud is costly to managers, reflecting effort costs and the chance that they may be caught and penalized.

In this simple model, the behavior of firms and investors depends heavily on the cost of monitoring and on investors' prior beliefs on the likelihood that any given firm is of good type. If investors' prior is low, they will be concerned that even a high signal has a significant chance of coming from one of the many bad firms in the economy. This being the case, even a high signal will not be funded without further monitoring, so that fraud yields no benefit to bad firms. As the prior improves, investors begin to fund high-signal firms without monitoring. Now fraud becomes attractive: by increasing the probability of a high signal, fraud increases the odds that a bad firm can get funding without the monitoring that would otherwise expose it. Fraud incentives continue to increase with the prior until high signals are never monitored and all bad firms commit fraud. If the prior increases further still, eventually there are so many good firms that the possibility that a low signal comes from an unlucky good firm is high enough to make unmonitored investment in a low-signal firm somewhat attractive. As the prior rises further, the probability with which low-signal firms are funded without monitoring increases. This means that, even without fraud, a bad firm has an increasing chance of being funded, so incentives to commit costly fraud decrease. If the prior is extremely high, investors may be willing to fund *all* firms without even paying attention to the free signal, in which case costly fraud has no benefit at all.

As monitoring costs fall, the thresholds for different "regimes" – fund high-signal firms without monitoring, fund low-signal firms without monitoring, etc. – are shifted towards better business conditions. Intuitively, fraud is only attractive when investors do not always monitor high-signal firms. Because lower monitoring costs make monitoring a more attractive option, the prior must be higher before investors cut back on monitoring high-signal firms. Paradoxically, the link between good times and fraud becomes stronger as monitoring costs fall.

Now suppose that investors are not perfectly informed on the relative frequency of good and bad firms: the relative frequency of good firms could be higher ("good state of the economy") or lower ("bad state of the economy") than their prior beliefs. Over time, actual firm successes and failures will reveal more information about the true state of the economy.

Suppose that the prior is low, so that investors put a high weight on the likelihood that the true state of the economy is bad rather than good. Later events will either reveal that the true state was bad, hence, a little worse than the prior, or reveal that, in fact, the prior was too pessimistic and there were many more good firms than expected. In the first case, there will not have been much fraud, since investors were suspicious to begin with and monitored heavily. In the second case, there will have been even less fraud in total, because bad firms were less frequent than suspected; indeed, ex post, the problem will be that many good firms that had low signals found it impossible to get funding.

By contrast, suppose that the prior is high enough that high-signal firms are not monitored, though low-signal firms are either monitored or not funded at all. If later events prove that the state of the economy was in fact good, there will not have been much fraud; bad firms did commit fraud, but there were few of them. On the other hand, if later events prove that the prior was too optimistic and the true state was bad, fraud will be prevalent; bad firms did commit fraud, and there were many more of them than expected. In this case, although some may later opine that the problem was that investors were insufficiently skeptical, investors in fact behaved rationally given their prior; the problem was that the true state of the economy was known only noisily and with a lag.

In fact, the economy evolves over time, so that the relative numbers of good and bad firms are always changing and investors are always updating their beliefs about these numbers. One source of information for such updating is free signals from firms. If these signals can be manipulated, then when bad firms commit fraud, free signals are noisier, and so rational investors are slower to update their beliefs. Supposing that a long stream of positive cash flows does eventually convince investors that times are likely to be good, it will be hard for them to detect when the tide has turned and the number of bad firms has increased – at least, until the projects of the bad firms have come off badly.

Thus, our model provides a rational explanation for why long booms often seem to end in a wave of failures and fraud. Saying that investors should know that the tide *can* turn is not the same as saying that they know *when* it has turned. So long as they think the boom is most likely to continue, they are justified in focusing their monitoring on low-signal firms. When the boom does end, ex post, many of the firms that have been funded will turn out to have committed fraud — but ex ante, the investors could not predict precisely when the boom would end and the number of bad firms would escalate.

Our model yields other counterintuitive predictions. When times are bad enough that high-signal firms are monitored with some probability, a decrease in the cost of monitoring increases monitoring and decreases fraud, as one would expect. By contrast, when times are good enough that monitoring focuses only on firms that produce low signals, a decrease in the cost of monitoring increases monitoring and *increases* fraud. This follows the intuition discussed before: fraud helps bad firms avoid low signals, and in good times, low signals are what triggers monitoring.

Again, this helps motivate behavior that at first glance seems completely myopic. In bad times (such as the early 1990s or right now), additional financing is hard to come by even for ventures with good ideas and track records. By contrast, in the good times of the late 1990s, shareholders and boards were routinely castigated in the business press for overreacting to bad news, so that the watchword for corporations was to avoid bad news at all costs. Yet even if the ongoing reduction in costs of telecommunication and computing have lowered the cost of analyzing firms, our model suggests that investors may optimally choose to focus their analysis on bad news in good times. If shareholders can only punish managers directly by selling stock (which may then trigger action by the board), then our model is consistent with the behavior that has been seen.

Although our model relies on fully rational behavior, we are not saying that investors are in reality fully rational. Instead, we are saying that fully rational behavior already exhibits features that are broadly in line with the facts. If investors are inclined to waves of excessive optimism and pessimism, this will further exacerbate these effects.

In addition to these "time series" effects, our model has cross-sectional implications for different industries during a given business cycle. For example, if investor priors in a given sector are extremely high, we should see little fraud; if priors in a sector are moderately high, then the potential for fraud increases. This may motivate differences between the "dot-com" and telecom industries during the boom of the 1990s. Investors were so willing to believe in the chances of success of any firm whose name that ended in "dot-com" that fraud per se was largely unnecessary. By contrast, in telecoms, investors, though optimistic, did pay attention to reported revenues and earnings; consistent with our prediction, this sector seems to have experienced far more cases of accounting fraud.

Our results also have policy implications. Regulators try to prevent or punish fraud that leads to the wasteful funding of bad firms. As we have shown, simply saying "buyer beware" may not do much to prevent fraud. Nevertheless, tougher disclosure standards can actually worsen the problem. If tougher disclosure standards improve the precision of free signals absent fraud, managers have more incentive to commit fraud to "noise things up." To be effective, disclosure standards must directly make fraud more difficult.

The plan of the rest of the paper is as follows. We discuss the relevant literature in Section 2. In Section 3 we introduce our model and key assumptions. In Section 4 we analyze the behavior of investors and firms in a setting where all agents know the underlying distribution of good and bad firms in the economy. In Section 5 we show how our results are affected by changes in the underlying parameters and how these can motivate actual behavior by firms and investors. We also show how agents' beliefs can be grounded in a framework in which the underlying state of the economy is unknown, leading to "surprising" volumes of fraud in certain circumstances. In Section 6 we discuss how our model's main results are robust to changes in our simple assumptions, and in Section 7 we conclude.

# 2 Literature Review

Although ours is the first paper that we are aware of that ties fraudulent behavior by firms to changing investor actions over the business cycle, there are a number of papers that are related to the tenor of our analysis. For example, a growing body of work examines "credit cycles" – the idea that banks and other credit suppliers engage in behavior that exacerbates business cycle effects, making credit even tighter in recessions, and looser in expansions, than pure demand-side effects would suggest. Among these, the closest to our paper is Ruckes (1998), who models how competing bank lenders' incentives to screen potential borrowers exacerbate cyclical variations in credit standards. None of these papers address borrower incentives to commit fraud, which is our key focus.

Another related paper is Persons and Warther's (1997) model of booms and busts in the adoption of financial innovations. In their model, individual firms decide whether to adopt a new financial technique based on the information that earlier adopters' experience noisily reveals. They show that such waves of adoption always end on a sour note, in the sense that the most recent adopters always lose money. Ex post, the information that ends the wave is always negative, but the timing of the end is ex ante random, and the latest adopters were behaving rationally based on the information available at the time. Like our model, this suggests that busts are always surprising yet may still be rational. Nevertheless, Persons and Warther do not address the role of fraud, and the mechanism of their model focuses on the evolution of social learning about a static innovation rather than investor-firm conflicts and behavior in the face of private information.

Four recent papers in the finance literature also focus on managerial incentives to commit fraud. Bebchuk and Bar-Gill (2002) present a model in which firms may commit fraud so as to obtain better terms when issuing shares to raise funds for further investments; this incentive to commit fraud increases if managers can sell some of their own shares in the short run or if accounting and legal rules are lax. Goldman and Slezak (2003) present a model where optimal managerial pay-for-performance contracts balance incentives to exert effort against incentives to commit fraud; increased regulatory penalties for fraud can sometimes increase the equilibrium incidence of fraud, and rules that reduce auditor incentives to collude with managers decrease the incidence of fraud but paradoxically reduce firm value. Subrahmanyam (2003) presents a model where more intelligent managers are better both at running firms and at committing successful (undetected) fraud; as a result, investors may prefer more intelligent managers and a higher incidence of fraud in exchange for higher average performance. Unlike our paper, these three papers do not examine how changes in economic conditions affect manager's incentives to commit fraud and investor's incentives to monitor managers, which is our primary focus.[1] Finally, Noe (2003) analyzes a different type of fraud, in which a firm's manager "tunnels" value from the firm into her own pocket. He focuses on providing the manager with incentives to perform rather than steal the funds that she has raised.

There are a number of studies in the accounting literature that focus on fraud incentives in the relationships between firms and their auditors. Some of these examine incentives to underreport earnings in order to hide managerial perquisite consumption; see for example Morton (1993). Closer to our focus are papers that examine the incentive to *over-report*; examples include Newman and Noel (1989), Shibano (1990), and Caplan (1999). Empirical work on SEC enforcement actions aimed at violations of Generally Accepted Accounting Principles (GAAP) suggests that over-reporting aimed at boosting share prices and improving access to additional capital is in fact the more frequent source of firm-wide financial misrepresentation.[2] Unlike our paper, these auditing papers on over-reporting focus on the impact of control systems and auditor incentives; they do not examine how fraud incentives change with overall business conditions. A further distinction is that auditors are typically penalized for failing to detect fraud. By focusing on the incentives of investors, we emphasize the fact that investors are not concerned with finding fraud per se, but rather with finding good investment opportunities. As already noted, this can lead to counterintuitive results when investors rationally focus their scrutiny on low signals rather than high ones.

Finally, our work contrasts with the growing literature that examines how bounded rationality can cause market overreactions. The critical difference is that our model relies on rational behavior throughout. As noted earlier, to the extent that deviations from rationality do lead investors' priors to overreact to recent information, they will exacerbate the effects

[1]Goldman and Slezak (2003) do show that an influx of naive, overly optimistic investors into the stock market increases the equilibrium incidence of fraud. Again, our model shows that such fluctuations can occur even when all investors are perfectly rational.

[2]For example, Peroz et al. (1991) find that fraud usually takes the form of earnings overstatement, and that news of an SEC enforcement action depresses stock price. Dechow et al. (1996) find that firms that commit fraud tend to have higher ex ante needs for additional funds.

we describe.

# 3 Basic Model and Assumptions

In this section we lay out the single period model that provides the framework for analyzing the incidence of fraud in Section 4. The economy consists of equal numbers of firm managers and investors, each of whom lives for one period. The sequence of events is summarized in Figure 1.

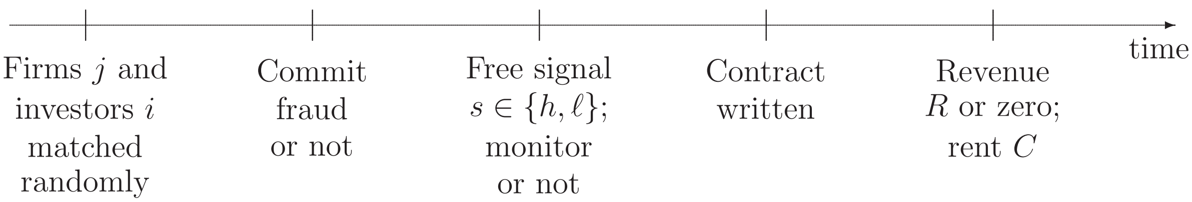


Figure 1: *Time line*

## 3.1 Firms and Managers

Each manager controls a firm that requires an investment of $I$ units of cash at the start of the period. At the end of the period, the firm returns a random contractable cash flow that equals $R > I$ with probability $\theta_i$ and zero with probability $1 - \theta_i$, where $i \in \{g, b\}$ is the firm's type. We assume that $0 \leq \theta_b < \theta_g < 1$. We also assume that

$$N_g = \theta_g R - I \ > 0 \qquad\qquad N_b = -(\theta_b R - I) > 0; \tag{1}$$

i.e., $g$ firms are positive net present value investments ("good"), whereas $b$ firms are negative NPV investments ("bad"). Note that $N_b$ is the *absolute value* of the expected loss from investing in a bad firm.

In addition to generating contractable cash flows, a funded firm generates $C$ in noncontractable control benefits which the manager consumes. This implies that, all else equal, a manager prefers to get her project funded, regardless of her firm's type.

Managers know their own firm's type, but outsiders can discover this only by monitoring the firm at a cost, as we discuss below. The prior probability that any given firm is good is given by $\mu$, where $\mu \in (0, 1)$. This prior is common knowledge. For the moment, we take this prior as exogenously given; we discuss how this can be embedded in a multi-period framework in Section 5.

## 3.2 Investors

Investors are each endowed with $I$ units of the generic good. At the beginning of the period, each investor is randomly matched with a manager and her firm. After being matched, the investor receives a free but noisy signal of the firm's type, and may then decide whether or not to expend additional effort and learn the firm's type more precisely. Based on any information that she has, the investor then can make a take-it-or-leave-it investment offer to the manager. The manager does not have time to approach another investor, so if the investor does not make her an offer, the manager cannot get funding for her firm.

Our assumptions of random matching and take-it-or-leave-it offers are made for simplicity; altering them would not change the essentials of our analysis. For simplicity, we also assume that investors cannot pay off bad firms to reveal their type; in practice, doing so is likely to be prohibitively expensive since a large number of incompetent managers would start firms and apply to investors for the sole purpose of receiving that payment. (We return to this issue of entry in Section 6 below.)

Thus, in equilibrium, if the investor does fund the firm, she receives all of the contractable cash flows that it produces. Nevertheless, since the manager receives control benefits $C$ if the firm is funded and nothing if the firm is not funded, she will take any offer that she is given.

## 3.3 Signals, Fraud, and Monitoring

As just mentioned, right after managers and investors are matched, each investor receives a free but noisy signal of the type of the manager's firm. This signal should be thought of as a financial report or a related public news release by the firm. We assume that this signal takes on one of two values, $h$ ("high") and $\ell$ ("low"). We also assume that, absent fraud, the signal is positively correlated with the firm's true type:

$$\Pr\{h|g\} = \gamma > \frac{1}{2} > \beta = \Pr\{h|b,\ \textit{no fraud}\}.$$

The free signal is subject to manipulation by the manager ("fraud"). The manager decides whether or not to commit fraud right after she and the investor are matched. Fraud costs the manager an amount $f$, where $f$ reflects both any effort involved in committing fraud and the chance that the manager is later caught and punished. We return to the issue of catching and punishing fraud in Section 6. Fraud increases the probability that a bad firm generates a high signal by $\delta < \gamma - \beta$; that is, $\Pr\{h\,|b,\ \textit{fraud}\} = \beta + \delta < \gamma$. Thus, fraud reduces the free signal's correlation with the firm's type, but the free signal remains somewhat informative.[3] Fraud is beneficial to the manager to the extent it increases the manager's chance of collecting control benefits $C$. It follows that fraud will never be attractive unless the cost of fraud f is less than the maximum possible benefit, i.e., $f < \delta C$. Henceforth, we assume that this condition holds.

In practical terms, fraud should be thought of as deliberate misstatement of the firm's results, either through altered financial reports or a misleading news release. Such an effort increases the odds that a casual glance at the firm's results will lead investors to think that the firm is in good shape – in terms of our model, it increases the probability that the public signal is high.

For simplicity, we assume that only bad firms commit fraud. As we discuss in Section 6, allowing good firms to commit fraud leaves most of our results qualitatively unchanged, so long as bad firms have relatively more to gain from fraud.

Suppose that the bad firm commits fraud with probability $\phi$. Let $\widehat{\mu}_s(\phi)$ be the investor's posterior probability that the firm is good after she sees the free signal $s$. Applying Bayes'

[3] Allowing $\delta$ to exceed $\gamma - \beta$ would have little effect on our qualitative results; bad firms would never commit fraud with certainty, but comparative statics would be unchanged.

Rule, we have

$$\widehat{\mu}_h(\phi) = \Pr[g|h] = \frac{\Pr\{g\}\Pr\{h|g\}}{\Pr\{g\}\Pr\{h|g\} + \Pr\{b\}\Pr\{h|b\}} = \frac{\mu}{\mu + (1-\mu)\frac{\beta+\phi\delta}{\gamma}}$$
$$\widehat{\mu}_\ell(\phi) = \Pr[g|\ell] = \frac{\Pr\{g\}\Pr\{\ell|g\}}{\Pr\{g\}\Pr\{\ell|g\} + \Pr\{b\}\Pr\{\ell|b\}} = \frac{\mu}{\mu + (1-\mu)\frac{1-\beta-\phi\delta}{1-\gamma}}.$$

Notice that $\forall\phi \in (0,1)$,

$$\widehat{\mu}_\ell(0) < \widehat{\mu}_\ell(\phi) < \widehat{\mu}_\ell(1) < \mu < \widehat{\mu}_h(1) < \widehat{\mu}_h(\phi) < \widehat{\mu}_h(0). \tag{2}$$

As expected, the posterior probability that the firm is good is higher after observing a high signal than it is after observing a low signal, and fraud makes the signal less precise, i.e. the posterior approaches the prior as either $\delta$ or $\phi$ increase.

After receiving the free signal, the investor can choose to investigate the firm further ("monitor"). Monitoring has an effort cost of $m > 0$ and perfectly reveals the firm's type. Once more, the assumption that monitoring is perfect is not essential; the key point is that monitoring gives more precise information about the firm's type, and that fraud distorts the information from monitoring relatively less that it distorts the free signal.

# 4 Investor and Firm Behavior

In this section, we analyze the equilibrium actions of the firm's manager (henceforth, "firm") and of the investor. As we will see, the incidence of fraud is hump-shaped, first increasing in the prior probability that firms are good, then decreasing. When this prior probability is below the point at which fraud reaches its peak, fraud increases as monitoring decreases; when the prior is above this peak, fraud and monitoring decrease together. The peak in fraud occurs for moderately good priors, and this peak shifts towards higher priors as monitoring costs decrease.

Our analysis proceeds via backwards induction. We begin with the investor's problem once she has observed the free signal; then we examine the firm's decision on whether to commit fraud before the free signal is sent. We conclude by characterizing the equilibrium levels of fraud and monitoring as functions of the prior probability that firms are good.

## 4.1 The Investor's Ex-Post Problem

After receiving the free signal $s$, the investor has three actions: she can choose not to invest (action "$N$"); she can monitor and then invest if the firm is good (action "$M$");[4] or she can invest without further monitoring (action "$U$" for unmonitored). Defining $V_A$ as the expected payoff to action $A$, these three actions' expected payoffs are as follows.

$$\begin{aligned} V_N &= 0 \\ V_M &= \widehat{\mu} N_g - m \\ V_U &= \widehat{\mu} N_g - (1-\widehat{\mu}) N_b \end{aligned}$$

It is immediate that the investor's decision depends only on the net present values $N_g$ and $N_b$ of the two types of firms, the cost of monitoring $m$, and the investor's posterior belief on the probability $\widehat{\mu}$ that the firm is good. For expositional ease, we define the following threshold probabilities: If $\widehat{\mu} = \frac{m}{N_g} \equiv \mu_1(m)$ then $V_N = V_M$; if $\widehat{\mu} = \frac{N_b}{N_b+N_g} \equiv \mu_2$ then $V_N = V_U$; and if $\widehat{\mu} = 1 - \frac{m}{N_b} \equiv \mu_3(m)$ then $V_M = V_U$. The next proposition describes the parameter regions in which the various actions are optimal.

**Proposition 1** *(Optimal Investor Actions Given Posterior Beliefs). Suppose that, after observing the free signal, the investor believes that the firm is good with probability $\widehat{\mu}$. The investor's optimal action is as follows:*

1. *Do not invest if $\widehat{\mu} < \min(\mu_1(m), \mu_2)$.*

2. *Invest without monitoring if $\widehat{\mu} \geq \max(\mu_2, \mu_3(m))$.*

3. *Monitor and invest if the firm is good if $\mu_1 < \widehat{\mu} \leq \mu_3(m)$ and $m < \frac{N_b N_g}{N_b+N_g} \equiv \overline{m}$.*

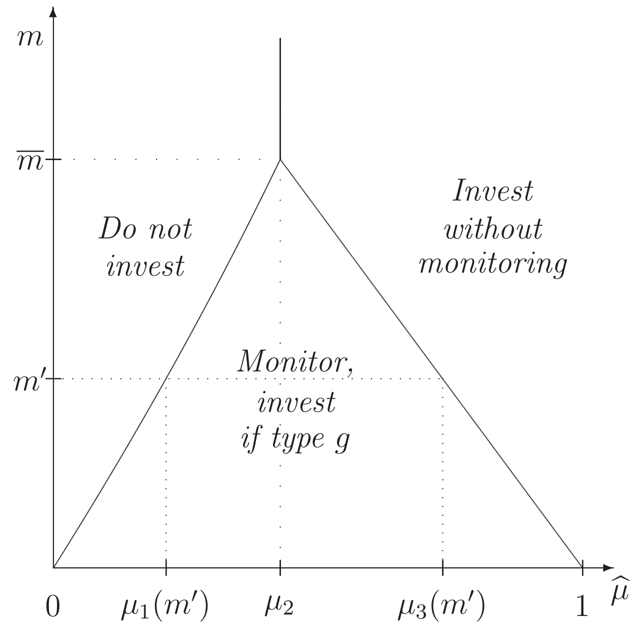


Figure 2: *Posterior probabilities and optimal investor decisions.*

Figure 2 displays key elements of the investor's decision problem. Given the realization of the free signal, the investor updates her beliefs about the firm's type. Together, the posterior $\widehat{\mu}$ and the cost of monitoring $m$ determine the optimal decision. If the cost of monitoring is above $\overline{m}$, then $\min(\mu_1(m), \mu_2) = \max(\mu_2, \mu_3(m)) = \mu_2$ and monitoring is always dominated by either not investing at all or unmonitored financing. Here, the investor provides unmonitored finance if and only if the posterior is above the threshold $\mu_2$, which determines where the investor is indifferent between not investing and unmonitored financing.

For monitoring costs below $\overline{m}$, it is possible that the expected benefit from monitoring (avoiding investing in bad firms and losing $N_b$) may exceed the cost of monitoring $m$. If $\widehat{\mu}$ is such that $m = \widehat{\mu} N_g$ (the upward sloping line in Figure 2), we have $V_N = V_M$, and the investor is indifferent between monitored finance and not investing. For example, if $m = m'$, the threshold for $\widehat{\mu}$ is $\mu_1(m')$. If $\widehat{\mu}$ is such that $m = (1 - \widehat{\mu}) N_b$ (the downward sloping line), we have $V_M = V_U$, and the investor is indifferent between monitored finance and unmonitored finance. For the example $m = m'$, this defines the threshold $\mu_3(m')$. It

[4] Note that, given (1), it never pays to invest in a bad firm.

follows that monitoring is optimal for intermediate posteriors, and the range of posteriors for which it is optimal increases as the cost of monitoring $m$ decreases.

Note that the investor's decision depends only on the posterior $\widehat{\mu}$, and not on *how* she forms this posterior; different combinations of the prior $\mu$ and the probability of fraud $\phi$ that lead to the same posterior $\widehat{\mu}$ lead to the same action.

## 4.2 The Manager's Decision to Commit Fraud

Having dealt with the investor's problem, we now examine the bad firm's decision on whether to commit fraud. This decision depends on the cost of fraud versus the expected benefit of fraud, which in turn depends on the investor's response as described in Proposition 1. Since monitoring detects bad firms, the firm only benefits from fraud if fraud increases the firm's probability of receiving unmonitored funding. Two conditions must be satisfied: *(i)* the investor's posterior after a high signal is such that the investor is willing to provide unmonitored funding, and *(ii)* the investor's posterior after a low signal is such that she provides unmonitored funding with strictly lower probability than that in the high-signal case. On the other hand, as mentioned in the previous section, in equilibrium, fraud makes the signal less precise, i.e. the posterior approaches the prior. This lessens the difference in impact between high and low signals, reducing the gains from fraud.

In equilibrium, the incidence of fraud must be consistent with incentives. Thus, if the manager's expected benefit strictly exceeds the cost $f$, she undertakes fraud with certainty ($\phi = 1$). If the benefit equals the cost, she is willing to commit fraud with positive probability ($0 < \phi < 1$). Otherwise, she does not commit fraud at all.

We first describe five different 'regimes' which characterize the equilibrium; which regime is relevant depends on the prior $\mu$ and to some extent on the cost of monitoring $m$. Define

$$\mu_{UF} = \max\left\{\mu_3\left(m\right), \mu_2\right\}.$$

From Proposition 1, $\mu_{UF}$ is the posterior at which the investor is indifferent between investing without monitoring and some other action. As noted above, unmonitored investment is critical to fraud. If the posterior is always above $\mu_{UF}$, there is no point to committing fraud; bad firms always get funding regardless of the signals they send. Similarly, if the posterior is always below $\mu_{UF}$, there is also no point to committing fraud; because firms never get funding without being monitored, bad firms cannot get funding regardless of the signals they send. Thus $\mu_{UF}$ is the key to equilibrium behavior, as we now show.

The regimes are defined as follows (the choice of names will become clearer below).

1. The Fund-Everything Regime: $\left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{1-\gamma}{1-\beta}\right)^{-1} \leq \mu < 1$.
2. The Optimistic Regime: $\left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{1-\gamma}{1-\beta-\delta}\right)^{-1} \leq \mu < \left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{1-\gamma}{1-\beta}\right)^{-1}$.
3. The Trust-Signals Regime: $\left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{\gamma}{\beta+\delta}\right)^{-1} \leq \mu < \left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{1-\gamma}{1-\beta-\delta}\right)^{-1}$.
4. The Skeptical Regime: $\left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{\gamma}{\beta}\right)^{-1} \leq \mu < \left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{\gamma}{\beta+\delta}\right)^{-1}$.
5. The No-Trust Regime: $0 < \mu < \left(1+\frac{1-\mu_{UF}}{\mu_{UF}}\frac{\gamma}{\beta}\right)^{-1}$.

There are two cases. In one case, monitoring is prohibitively costly, i.e. $m > \overline{m}$; in the other, $m < \overline{m}$, and the firm may monitor in equilibrium. We begin with the case where monitoring is possible.

**Proposition 2** *Assume $m \leq \overline{m} = \frac{N_b N_g}{N_b+N_g}$. Denote by $\lambda_s$ the probability of monitoring with a signal $s$, by $\kappa_s$ the probability of unmonitored finance with a signal $s$, and by $\phi$ the bad firm's probability of committing fraud. The equilibrium decisions are as follows:*

1. *Fund-Everything Regime. The investor never monitors ($\lambda_h = \lambda_\ell = 0$), all firms are funded regardless of the signal ($\kappa_h = \kappa_\ell = 1$), and there is no fraud ($\phi = 0$).*
2. *Optimistic Regime. High-signal firms are always funded without monitoring ($\lambda_h = 0$ and $\kappa_h = 1$). Low-signal firms are funded without monitoring with probability $\kappa_\ell = 1 - \frac{f}{\delta C}$ and are monitored otherwise ($\lambda_\ell = \frac{f}{\delta C}$). Bad firms commit fraud with probability $\phi = \frac{1}{\delta}\left(1-\beta-\frac{\mu}{1-\mu}\frac{m}{N_b-m}(1-\gamma)\right)$.*

3. *Trust-Signals Regime. High-signal firms are always funded without monitoring ($\lambda_h = 0$ and $\kappa_h = 1$). Low-signal firms are never funded without monitoring ($\kappa_\ell = 0$). Bad firms always commit fraud ($\phi = 1$).*

4. *Skeptical Regime. High-signal firms are funded without monitoring with probability $\kappa_h = \frac{f}{\delta C}$ and are monitored otherwise ($\lambda_h = 1 - \frac{f}{\delta C}$). Low-signal firms are never funded without monitoring ($\kappa_\ell = 0$). Bad firms commit fraud with probability $\phi = \frac{1}{\delta}\left(\frac{\mu}{1-\mu}\frac{m}{N_b - m}\gamma - \beta\right)$.*

5. *No-Trust Regime. Firms are never funded without being monitored ($\kappa_h = \kappa_\ell = 0$) and there is no fraud ($\phi = 0$).*

**Proof.** See the Appendix. ■

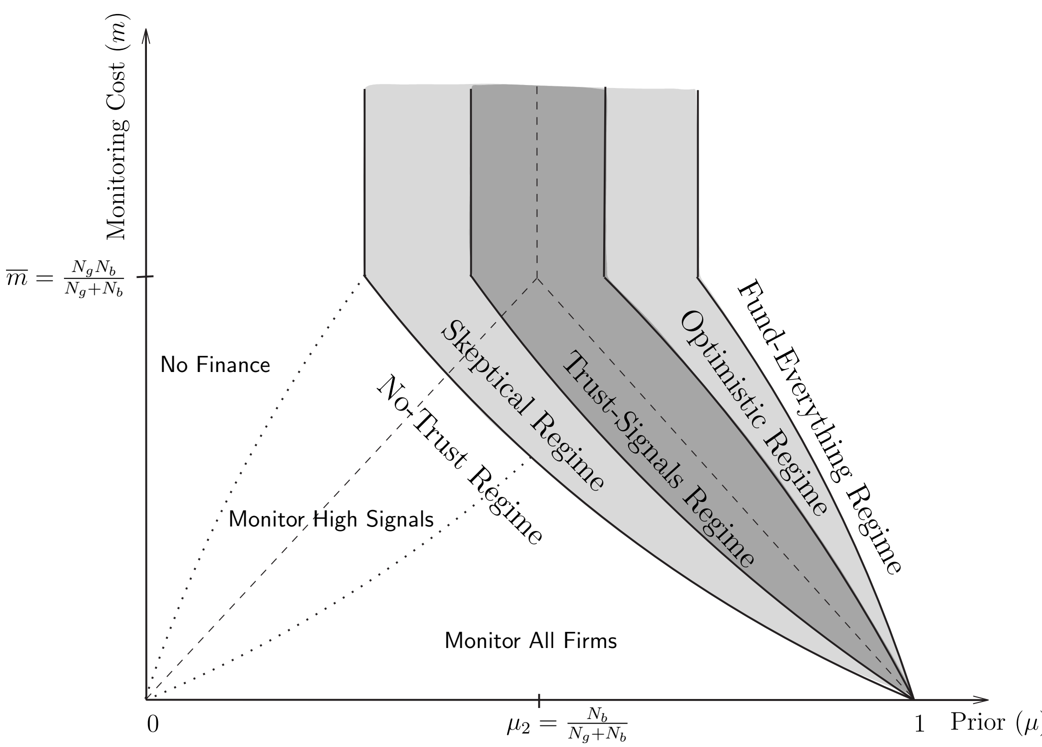


Figure 3: *Five Regimes.*

Figure 3 shows which $(\mu, m)$ pairs fall into each regime, both for the case where monitoring is feasible, as described in the preceding proposition, and for the case where monitoring is prohibitively expensive, as described in Proposition 3 below. The darker shaded region consists of all $(\mu, m)$ pairs for which bad firms find it optimal to commit fraud with certainty. In the lighter shaded regions, bad firms commit fraud with probability strictly between zero and one. In the unshaded regions, there is no fraud at all.

Returning to Proposition 2, the boundaries of the five regimes depend on $\widehat{\mu}_s(\phi)$, which again is the investor's posterior belief that the firm is good after seeing the free signal $s$ and assuming that the bad firm commits fraud with probability $\phi$. In the *Fund-Everything* regime, the prior $\mu$ is so high that the investor is willing to provide unmonitored finance regardless of the signal. In this case, the fraction of good firms in the population is so high that even a low signal is very likely to have come from a good firm. Since all firms are funded, there is no benefit from committing fraud in this regime.

In the *Optimistic* regime, either the prior $\mu$ or the cost of monitoring $m$ is somewhat lower. Here, a high signal still leaves the investor choosing to fund the firm without monitoring, but a low signal is bad enough that the investor prefers to monitor with some probability.[5] In this regime, monitoring actually encourages fraud, since bad firms that produce a low signal may be monitored and denied funding.

In the *Trust-Signals* regime, $\widehat{\mu}_\ell(1) < \mu_3(m) < \widehat{\mu}_h(1)$. Here, only high signals receive unmonitored finance; low signals are either monitored or rejected (the choice depends on whether or not $\widehat{\mu}_\ell(0)$ exceeds $\mu_1(m)$). Either way, bad firms are not financed if they produce a signal $\ell$, so their incentive to commit fraud is higher than it would be in the *Optimistic* regime. In this regime, they commit fraud with certainty.

With lower values of $\mu$ or $m$, we enter the *Skeptical* regime. In this regime, $\widehat{\mu}_h(1) < \mu_3(m) < \widehat{\mu}_h(0)$. The priors in this regime are low enough that the investor finds it optimal to monitor even high signals with positive probability. Because the bad firm may not get financing even if it manages to obtain a high signal, the gains from fraud are lower than those in the *Trust-Signals* regime. Thus bad firms commit fraud with probability strictly

[5] More precisely, in the *Optimistic* regime we have $\widehat{\mu}_\ell(0) < \mu_3(m) < \widehat{\mu}_\ell(1)$. If there were no chance of fraud in equilibrium, the investor would strictly prefer to monitor after a low signal; if there were fraud with certainty, the investor would strictly prefer to not monitor; thus, in equilibrium, the investor monitors with probability between 0 and 1.

less than one.

Finally, for very low values of $\mu$, $\widehat{\mu}_h(0) < \mu_3(m)$. In this *No-Trust* regime, investor's posteriors are so low that all firms are either monitored or rejected, regardless of the signal. Since there is no unmonitored finance, there is no gain to committing fraud, and so there is no fraud in equilibrium.

Figure 3 is related to Figure 2, which shows the details of the investor's ex-post decision problem. The dashed lines in Figure 3 are equivalent to the solid lines in Figure 2. Our focus is on the fraud decision: fraud is committed with positive probability in the vicinity of the downward sloping line in Figure 2; the closer the pair $(m, \mu)$ to this line, the higher (weakly) the probability of fraud. Thus fraud is most rewarding when from the investor's perspective, the ex ante difference between monitoring and providing unmonitored finance is small.

The regimes described in Proposition 2 extend into the region with prohibitively high $m$ in a natural way (see Figure 3):

**Proposition 3** *Assume $m > \overline{m} = \frac{N_b N_g}{N_b + N_g}$, so that the investor never monitors. Denote by $\kappa_s$ the probability of unmonitored finance with a signal $s$, and by $\phi$ the bad firm's probability of committing fraud. The equilibrium decisions are as follows:*

1. *Fund-Everything Regime. All firms are funded regardless of the signal ($\kappa_h = \kappa_\ell = 1$), and there is no fraud ($\phi = 0$).*

2. *Optimistic Regime. High-signal firms are always funded ($\kappa_h = 1$). Low-signal firms are funded with probability $\kappa_\ell = 1 - \frac{f}{\delta C}$ and denied funding otherwise. Bad firms commit fraud with probability $\phi = \frac{1}{\delta}\left(1 - \beta - \frac{\mu}{1-\mu}\frac{N_g}{N_b}(1-\gamma)\right)$.*

3. *Trust-Signals Regime. High-signal firms are always funded ($\kappa_h = 1$). Low-signal firms are never funded ($\kappa_\ell = 0$). Bad firms always commit fraud ($\phi = 1$).*

4. *Skeptical Regime: High-signal firms are funded without monitoring with probability $\kappa_h = \frac{f}{\delta C}$ and denied funding otherwise. Low-signal firms are never funded ($\kappa_\ell = 0$). Bad firms commit fraud with probability $\phi = \frac{1}{\delta}\left(\frac{\mu}{1-\mu}\frac{N_g}{N_b}\gamma - \beta\right)$.*

5. *No-Trust Regime: firms are never funded* ($\kappa_h = \kappa_\ell = 0$) *and there is no fraud* ($\phi = 0$).

**Proof.** See the Appendix. ■

If $m > \overline{m}$, monitoring is prohibitively expensive, and the investor either rejects the firm or provides unmonitored financing. The five regimes are completely analogous to those in Proposition 2. The main difference is that if a regime calls for monitoring when $m \leq \overline{m}$, it calls for denying funding when $m > \overline{m}$.

Our next result is a straightforward consequence of Propositions 2 and 3.

**Proposition 4** *Both the probability of fraud $\phi$ conditional on the firm being bad, and the ex-ante probability of fraud $(1-\mu)\,\phi$ are hump-shaped in the prior $\mu$. There is no fraud for the highest and lowest levels of $\mu$, the* Fund-Everything *and* No-Trust *regimes. In the* Skeptical *regime the probabilities of fraud are increasing in $\mu$, while in the* Optimistic *regime they are decreasing. In the* Trust-Signals *regime, the conditional probability is constant, while the ex-ante probability is decreasing in $\mu$.*

**Proof.** See the Appendix. ■

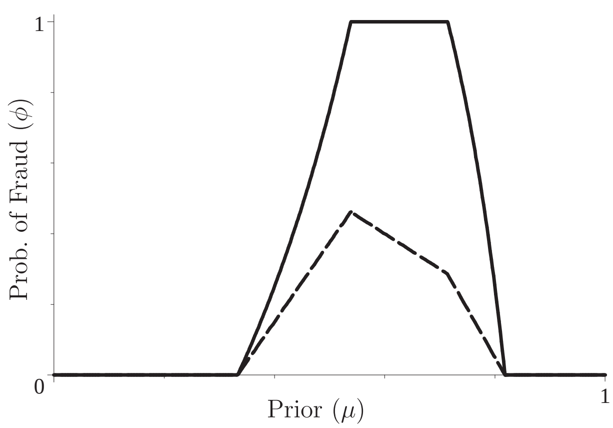


Figure 4: *Fraud probability: ex-ante (dashed line) and conditional (solid line).*

Figure 4 shows the conditional and ex-ante probabilities of fraud. The graphs consist of five parts, corresponding to the five regimes described above. In the *Skeptical* regime, the probabilities increase with $\mu$. High-signal firms are monitored or denied funding with positive probability, low-signal firms with certainty. Thus the investor is indifferent between monitoring (or denying funding to) high-signal firms and funding them without any further information. All else equal, an increase in the prior $\mu$ makes the investor strictly unwilling to monitor (or deny funding to) high-signal firms – but then the bad firm would prefer to commit fraud with certainty, worsening the pool of high-signal firms and destroying equilibrium. In equilibrium, the probability of fraud must increase so as to restore balance.

In the *Optimistic* regime, the probabilities *decrease* with $\mu$. The investor strictly prefers to fund high-signal firms, and is indifferent between monitoring (or denying funding to) low-signal firms and funding them without further information. Here, an increase in the prior makes the investor strictly prefer to fund low-signal firms without monitoring – but then bad firms would have no reason to commit fraud, worsening the pool of low-signal firms and destroying equilibrium. In equilibrium, the probability of fraud decreases so as to restore balance.

This accounts for the results on the bad firms' conditional probability of fraud $\phi$; the results on the ex ante probability of fraud $(1 - \mu)\,\phi$ follow immediately.

# 5 Determinants of Fraud

Having established the properties of equilibria in the various regimes, we now turn to the question of how various parameters affect the incidence of fraud. We show that, while certain results are constant across regimes, others depend heavily on whether the regime is *Skeptical* or *Optimistic*. In particular, the *Skeptical* regime is the more intuitive case; here, monitoring discourages fraud, and other parameter effects are as one would expect. By contrast, the *Optimistic* regime is counterintuitive; here, monitoring *encourages* fraud, and several parameter effects are the reverse of what one would expect. We then turn to a discussion of how our results are affected by dynamic considerations.

We begin with the comparative statics of the *Skeptical* regime.

**Proposition 5** *In the* Skeptical *regime,*

*(i) The equilibrium probability that bad firms commit fraud ($\phi$) is increasing in the prior $\mu$, weakly increasing in the cost of monitoring $m$, and decreasing in the efficacy of fraud $\delta$. It is increasing in the probability that good firms send high signals ($\gamma$) and decreasing in the base probability that bad firms send high signals ($\beta$).*

*(ii) If the monitoring cost is low ($m \leq \overline{m}$), then the equilibrium probability that high-signal firms are monitored ($\lambda_h$) is decreasing in the cost of fraud $f$ and increasing in both the efficacy of fraud $\delta$ and in the level of private benefits $C$. If the monitoring cost is high ($m > \overline{m}$), then the equilibrium probability that high-signal firms are denied funding is decreasing in the cost of fraud $f$ and increasing in both the efficacy of fraud $\delta$ and in the level of private benefits $C$.*

The intuition for part *(i)* of the proposition follows from the effects of parameter changes on the investor's incentives to monitor the pool of firms that generate high signals. An increase in the prior probability that firms are good or an increase in the probability that good firms generate high signals improves the pool, lowering the investor's incentives to monitor or deny funding. This allows the probability that bad firms commit fraud ($\phi$) to increase until equilibrium is restored. An increase in the efficacy of fraud or an increase in the base probability that bad firms generate high signals has the opposite effect. Finally, if monitoring costs are sufficiently low ($m \leq \overline{m}$), an increase in the cost of monitoring directly lowers the investor's monitoring incentives, again allowing the probability of fraud to increase. (If $m > \overline{m}$, the investor never monitors, so changes in $m$ have no effect on the probability of fraud.)

The intuition for part *(ii)* of the proposition is straightforward. The probability of monitoring or funding denial is determined by the bad firm's incentive condition – the point at which it is indifferent between committing fraud and not committing fraud. If the cost of fraud increases, then fraud is less attractive, and less intensive monitoring or less frequent funding denial suffices to deter fraud to the point of indifference. Higher private benefits make getting funded more attractive. Because generating a high signal is the only way that a bad firm has a chance of getting funded, fraud is more attractive, and again more intensive monitoring or funding denial is needed. Finally, if fraud is more effective, the pool of high-signal firms worsens, all else equal, and more intensive monitoring or funding denial is needed to restore balance.

As noted above, the *Skeptical* regime is the intuitive case. The investor's decision about partial monitoring or funding denial focuses on firms with high signals, and fraud gives a bad firm a higher chance of entering this pool and getting funding. This leads to a direct link between the intensity of monitoring or funding denial and fraud incentives. By contrast, the *Optimistic* case is less intuitive. Here, partial monitoring or funding denial focuses on firms with low signals, and fraud gives a bad firm a higher chance of *exiting* this pool by generating a high signal and getting automatic funding. Thus, the link between the intensity of monitoring and fraud incentives is now less direct. This can be seen in the following proposition.

**Proposition 6** *In the* Optimistic *regime,*
*(i) The equilibrium probability that bad firms commit fraud ($\phi$) is decreasing in the prior $\mu$ and the efficacy of fraud $\delta$, and weakly decreasing in the cost of monitoring $m$. It is increasing in the probability that good firms send high signals ($\gamma$) and decreasing in the probability that bad firms send high signals ($\beta$).*
*(ii) If the monitoring cost is low ($m \leq \overline{m}$), then the equilibrium probability that low-signal firms are monitored ($\lambda_\ell$) is increasing in the cost of fraud $f$ and decreasing in both the efficacy of fraud $\delta$ and in the level of private benefits $C$. If the monitoring cost is high ($m > \overline{m}$), then the equilibrium probability that low-signal firms are denied funding is increasing in the cost of fraud $f$ and decreasing in both the efficacy of fraud $\delta$ and the level of private benefits $C$.*

As before, part *(i)* of the proposition follows from the effects of parameter changes on the investor's incentives to tighten funding (i.e., monitor or deny funding, depending on whether or not $m \leq \overline{m}$) for the pool of firms with low signals. An increase in the prior probability that a firm is good increases the fraction of low-signal firms that are good, reducing the investor's incentives to tighten funding. Since a reduction in monitoring or funding denial makes fraud less attractive (bad firms are more likely to be funded even if they get a low signal), the probability of fraud falls until incentives are restored. An increase in the probability that bad firms generate high signals — either with fraud ($\beta+\delta$) or without it ($\beta$) — also increases the fraction of low-signal firms that are good, discouraging fraud. Conversely, an increase in the probability that good firms generate high signals worsens the pool of low-signal firms, increasing the investor's incentives to tighten funding and thus encouraging fraud. Finally, if monitoring costs are sufficiently low ($m \leq \overline{m}$), an increase in the cost of monitoring directly lowers the investor's monitoring incentives, discouraging fraud.

Part *(ii)* follows from the effects of parameter changes on the bad firm's incentives to commit fraud. The difference is that now, more intensive monitoring or more frequent funding denial decreases the probability that a bad firm with a low signal gets funded, and so tighter funding *encourages* bad firms to commit fraud so as to improve their odds of generating high signals. When fraud is more costly, fraud is less attractive, so more of the low-signal firms are in fact bad firms, and tighter funding is required to restore equilibrium. Conversely, since more effective fraud or higher private control benefits increase the quality of the pool of low-signal firms, looser funding is required to restore equilibrium.

## 5.1 Implications

We now turn to some direct implications of our model. Perhaps the most striking result is the way that many parameter changes have opposite effects depending on whether the equilibrium is *Skeptical* or *Optimistic*. As already suggested, this occurs because of the differing focus of investor scrutiny in these two regimes. In "skeptical" times, investors strictly prefer to be "tough" (monitor or deny funding) with low-signal firms, but they are somewhat "looser" with high-signal firms. As a result, changes in parameters affect investors' behavior with high-signal firms but not with low-signal firms. The opposite is true in "optimistic" times: now, investors strictly prefer to fund high-signal firms, but they apply somewhat tougher standards to low-signal firms. In this case, changes in parameters affect investors' behavior with low-signal firms but not with high-signal firms, and so the effects of many parameter changes switch sign.

The results on monitoring in the *Optimistic* regime seem counterintuitive because we tend to think of monitoring as focusing on detecting fraud. Of course, our model is very stylized, but the underlying point is an important one: monitoring by investors is directed at finding good investment opportunities, not detecting fraud per se. In the *Optimistic* regime, the chance that a high signal comes from a good firm outweighs the chance that it comes from a bad firm that has committed fraud. As a result, investors begin to loosen funding standards for low-signal firms. Changes that further loosen these standards actually discourage fraud because bad firms see less need for it – why commit fraud when you can get funded without it?

Similarly counterintuitive results arise from changes in the underlying prior that firms are good. In the *Skeptical* regime, an increase in this prior loosens funding standards and encourages fraud, which is what we think of as normal behavior. By contrast, in the *Optimistic* regime, an increase in the prior loosens funding standards and *discourages* fraud. Again, if investors are sufficiently optimistic, there is less need for fraud to attain funding.

This last result may provide a partial explanation for what happened during the 1990s boom; arguably, as information technology improved, it became easier for analysts and others to "kick the tires" — but during the boom these efforts were concentrated on firms that were known as poor performers. Perversely, this may have increased the prevalence of fraud.

Another implication comes from the result that, as the cost of monitoring falls, the region where fraud occurs shifts towards better prior beliefs (see Figure 3). This suggests that as telecommunications and information processing costs have come down, the incidence of fraud may be even more tilted towards better states of the world.

Our model is also consistent with differences in lending behavior across the business cycle. The literature on credit cycles shows that lenders are more willing to make "Type I" errors (rejecting or rationing good credits) in recessions, and more willing to make "Type II" errors (lending to bad credits) in expansions. This is consistent with broad differences between the

*No-Trust* and *Skeptical* regimes on the one hand and the *Optimistic* and *Fund-Everything* regimes on the other. Although our model is not unique in predicting this result, it serves as a useful reality check.

More interestingly, our results also have applications to the prevalence of fraud in different sectors. In the late 1990s, Internet or "dot-com" firms were viewed as "can't miss" opportunities, because of a widespread conviction that much conventional business would migrate to the Internet in a relatively short period of time. Leaving aside the question of whether so strong a conviction was rational, this view led to the financing of many start-ups that did not even have business plans (see e.g. Schenone, 2003). Yet there have been few accusations of fraud directed at the Internet firms. By contrast, the telecoms sector, though viewed very positively, was not the subject of such strong optimism in the 1990s. Recently, numerous large telecoms firms (including WorldCom, Qwest, Global Crossing, and Lucent) have been accused of fraudulent or misleading accounting. This difference is consistent with our model: Internet firms may have fallen into or close to the *Fund-Everything* regime, in which case there was no need to commit fraud, whereas the telecoms may have fallen into the lower *Optimistic* regime, in which case fraud should have been expected.

Although our analysis suggests that there is an interesting contrast between "optimistic" and "skeptical" regimes, some parameter effects are the same in both. In particular, the probability of fraud increases in the probability $\gamma$ that good firms send high signals and decreases in the probability $\beta$ that bad firms send high signals and in the efficacy of fraud $\delta$. As discussed above, changes in these "signal quality" parameters change the pool of high- and low-signal firms in such a way that they have consistent effects on bad firms' choice between committing fraud and not committing fraud. For example, an increase in $\gamma$ increases the number of good firms in the high-signal pool and reduces the number in the low-signal pool. In the *Skeptical* regime, the improvement in the high-signal pool reduces funding stringency and encourages fraud; in the *Optimistic* regime, the worsening of the low-signal pool increases funding stringency and again encourages fraud.

These results on signal quality suggest that an improvement in the precision of the "base" or "raw" signal (i.e., an increase in $\gamma$ and decrease in $\beta$) should increase the prevalence of fraud. Intuitively, a more precise signal means that the bad firm has more chance of being revealed, which gives it more incentive to try to hide matters by committing fraud and "noising up" the signal. By contrast, an increase in the efficacy of fraud makes investors pay less attention to the free signal, increasing the odds that a bad firm will either be denied funding outright or else monitored with the same end result.

The signal quality results also have implications for policy makers. Suppose that regulators decide to toughen disclosure standards. If tougher disclosure means releasing more details that give investors a better sense of the firm's situation, bad firms will be less able to get funding unless they fraudulently alter their results. Something of this sort may have happened in the 1990s. The general trend throughout the decade was for annual reports to release more and more details in the notes to the financial statements, in large part in response to demands for greater revelation from the Financial Accounting Standards Board (FASB). Although many complained that notes were becoming denser, the point is that audited information that was not previously available was now disclosed. In the absence of fraud or misrepresentation, investors could now do a better job of assessing a firm's situation — and so a number of firms began to game the system, in many cases crossing the line into fraud. Thus, tougher disclosure laws can have the perverse effect of increasing fraud.

## 5.2 Dynamic Considerations

Up until now, we have assumed that investors and firms know the prior distribution of firm types without uncertainty. In practice, such priors are likely to be uncertain, since the "true" state of the economy can only be known ex post, if at all. Moreover, the true state of the economy is dynamic, which can complicate the inference problems of investors and managers. As suggested in the introduction, these considerations can exacerbate the links between fraud, booms, and busts.

To model these issues in a simple way, we assume that there are two possible true states of the economy, one in which there are relatively many good firms (fraction $\mu_u$ of all firms) and one in which there are relatively few good firms (fraction $\mu_d$ of all firms, with $\mu_d < \mu_u$). Furthermore, we assume that $\mu_u$ falls into the *Fund-Everything* regime, and $\mu_d$ falls into the *No-Trust* regime. The true state cannot be observed, and all agents share common beliefs: the probability that the state is $\mu_u$ is $p_0$. It follows that the overall prior that any given firm is good is $\mu = p_0\mu_u + (1 - p_0)\mu_d$.

First suppose that $p_0$ is low. In this case, the ex-ante prior $\mu$ is low, corresponding to either the *No-Trust* or (low) *Skeptical* regime. Bad firms are unlikely to commit fraud in this case, since even high-signal firms are usually monitored before they are financed. If, ex post, the true state of the economy proves to be $\mu_d$, there will be slightly more bad firms than expected, but the overall incidence of fraud will still be low or nonexistent. If instead the true state proves to be $\mu_u$, there will be even fewer cases of fraud, funded projects will be relatively successful, and investors' conservatism may seem overblown, as more monitored projects than expected will prove to be good.

Now suppose $p_0$ is high, so that the ex-ante prior $\mu$ falls within the *Trust-Signals* or *Optimistic* regime. Although bad firms will be committing fraud, if the true state later proves to be $\mu_u$, there will not be many bad firms, and the actual incidence of fraud will be somewhat lower than expected. By contrast, if the true state proves to be $\mu_d$, the numbers of bad firms and fraud cases will be much higher than expected.

If the prior is higher still, of course, the equilibrium will fall into the upper end of the *Optimistic* regime or even the *Fund-Everything* regime. In this case, fraud will be low or nonexistent, even if the state proves to be $\mu_d$, but in this last case many more funded projects than expected will perform poorly.

All of this has taken $p_0$ as given. In reality, $p_0$ will arise from investors getting signals from various firms and from some "actual" realizations (e.g., realized cash flows in our model). Note that the presence of fraud slows down updating in both directions: both high and low signals become noisier. Thus, priors will be slower to shift in the "middle," where bad firms are likely to commit fraud. If beliefs begin with a $p_0$ so high that the regime is *Fund-Everything*, and then some bad realizations of the free signal shift $p_0$ and thus $\mu$ into the

*Optimistic* or *Trust-Signals* regime, further updating will be slowed.

If there were no change in the underlying state, then over time, investor beliefs would find their way to the true state. A more realistic assumption is that there is always some chance that the underlying state governing the returns on new projects can shift – some chance of transitioning from $\mu_d$ to $\mu_u$, and another chance of transitioning the other way. If by some chance beliefs do find their way close to one or the other extreme, there will always be some chance that the beliefs are "very wrong" due to a transition. Of course, these transition probabilities limit how high or low $p_0$ can go, but there is still a chance that beliefs will be heavily weighted towards one extreme or the other, in which case "surprises" of the sort already discussed will still be possible. In particular, once $p_0$ and thus $\mu$ are in the *Optimistic* regime, a period of slow updating from "free" signals (interim results) could be followed either by a reassuring string of high cash flows or a spate of low cash flows that suddenly reveal that the economy is in recession – followed in the last instance by a wave of revelations of fraud.

In short, the agents in an economy may be "surprised" by changes in the economy's fundamentals. Although this notion is not especially surprising, it has strong implications for the incidence and prevalence of fraud across the business cycle. As noted, when times are bad — in terms of our model, in the *No-Trust* or *Skeptical* regimes — positive surprises will lead to lower amounts of fraud than expected. The opposite is true when times are good; now surprises lead to higher-than-expected fraud.

It is also important to note that, in the last case, even fraudulent firms are surprised by the extent of fraud. Although they have private information that they are in bad shape, which is a *somewhat* negative signal for the economy as a whole, this is not the same as knowing that many firms are in bad shape. In a more complex model, this can lead to negative spillovers as firms with weak prospects who see others post high results feel more pressure to do so themselves, precisely because neither they nor investors know whether the others are committing fraud. Something of this sort seems to have happened in the case of WorldCom, whose fraudulent reporting in the 1990s increased the pressure on its rivals

(Schiesel, 2002).

# 6 Robustness and Extensions

In order to streamline our exposition, our analysis has made use of several simplifying assumptions. In this section, we discuss the consequences of loosening three of these: the assumption that the relative numbers of good and bad firms are fixed exogenously, the assumption that the cost of fraud is fixed exogenously, and the assumption that only bad firms commit fraud. As we will see, allowing for endogenous entry or costs of fraud that depend on the probability of getting caught do not change the thrust of our results. Allowing good firms to commit fraud does not change most of our results, but sometimes causes complications that could be resolved in a richer model.

## 6.1 Allowing Entry and Exit of Firms

Our model has assumed that the distribution of good and bad firms – encapsulated in the prior $\mu$, which is the proportion of good firms in the economy – is fixed exogenously. Based on the experience of the 1990s boom, however, one might argue that these numbers should be somewhat flexible, as changing beliefs lead to exit and entry by firms. For example, optimistic beliefs on the part of investors and managers should lead to more entry, especially by managers of bad firms. To the extent investors anticipate this, this should limit just how optimistic beliefs about the distribution of firms can be. Conversely, pessimistic beliefs should lead to exit, especially by bad firms; this would limit how pessimistic beliefs can be.

Suppose then that the initial distribution of firms is weighted towards good firms; to be specific, the initial proportion of good firms is $\mu_0$, where $\mu_0$ is in the *Fund-Everything* regime. Managers with bad potential projects should then enter the market, bearing any costs of seeking funds (getting matched with an investor) in the hopes of getting control benefits. If investor beliefs did not change, such entry would continue until the supply of potential bad firms is exhausted or the marginal bad firm has a cost of seeking funds equal to the control benefit $C$. If investors are rational, however, such entry will depress their prior from $\mu_0$ to some lower $\mu_1$. The prior might fall enough to cross into the *Optimistic* regime or even lower, where firms are sometimes monitored or denied funding; this would lower the probability that bad firms could get funding, making entry less attractive and lowering the critical cost of seeking funds at which entry is just attractive.

At the other extreme, suppose that the initial distribution is weighted towards bad firms: $\mu_0$ falls into the *No-Trust* regime. In this case, either investors may choose to fund no one, or, if monitoring costs are sufficiently low, firms can only get funded if they are monitored first. In the first case, all firms would exit rather than incur costs of seeking funds, leaving the economy in autarky. In the second case, only bad firms would exit; this would raise the prior, possibly moving the economy into a regime where bad firms have some chance of being funded (and thus lowering the cost of seeking funds at which a bad firm is indifferent to exiting or staying in the market).

From this discussion, it is obvious that the number of potential bad firms and the distribution of their costs of seeking funds would be key factors. So long as the supply of firms (and especially bad firms) is somewhat inelastic, however, our main results would be unaffected: very optimistic or pessimistic beliefs might not be sustainable in equilibrium, but there would still be a range of equilibrium priors supporting the different regimes we have analyzed.

### 6.2 Explicit Detection of Fraud

We have assumed that fraud has a fixed cost $f$. This is consistent with a model in which fraud has some fixed effort cost $\varepsilon$, after which it may be detected by the authorities with fixed probability $\alpha$ and fixed punishment (if caught) $P$, such that $\varepsilon + \alpha P = f$. In practice, however, this formulation is overly simplistic. If a firm is actually funded, transaction data is generated and future performance may be scrutinized and compared to earlier reports; thus, the authorities may find it easier to catch fraud committed by firms that are actually funded. Similarly, investors who monitor should have a better chance of detecting possible fraud than do investors who rely completely on the free signal.

Accordingly, suppose that the probability of being caught after committing fraud, $\alpha$, varies directly with the probability that the (bad) firm is funded and with the probability that the firm is monitored: with probability $\omega > 0$, the regulatory authorities (such as the SEC) catch fraudulent firms that are funded without being monitored, and with probability one, investors catch fraudulent firms that they monitor. (Implicitly, we are assuming that the authorities cannot investigate all funded transactions.) Then the probability of being caught is $\alpha = (\beta+\delta)(\kappa_h\omega+\lambda_h)+(1-\beta-\delta)(\kappa_\ell\omega+\lambda_\ell)$, where once more $\kappa_s$ is the probability of getting unmonitored funding when the free signal is $s$ and $\lambda_s$ is the probability of being monitored when the free signal is $s$. Given an effort cost $\varepsilon$ for committing fraud, it follows that the total cost of committing fraud is still $f = \varepsilon + \alpha P$, but now $\alpha$ depends on the probabilities with which firms are monitored and with which they are given unmonitored funding.

This does not affect the basic outline of our results. To see why, note that the firm's decision to commit fraud is based on the gain from committing fraud versus the cost. In our simple model, the gain is the expected increase in the chance of getting unmonitored funding times the control benefit, or $\delta(\kappa_h - \kappa_\ell)C$; the cost is $f = \varepsilon + \alpha P$. It is easy to show that if $\delta C < \varepsilon + (\beta + \delta)\omega P$, the benefit $\delta(\kappa_h - \kappa_\ell)C$ is always less than the cost $\varepsilon + \alpha P$, so fraud is never attractive. Consistent with our emphasis before, we will assume that $\delta C$ exceeds $\varepsilon + (\beta + \delta)\omega P$ so that fraud is in fact possible.

First, consider the case where monitoring costs are so high that investors never monitor ($m > \overline{m}$). It is easy to show that, in this region, the boundaries of the five regimes are precisely as before. For example, in the *No-Trust* regime, $\kappa_h = \kappa_\ell = 0$, so there is no incentive to commit fraud. The boundary between this regime and the *Skeptical* regime is the point at which unmonitored funding for high-signal firms is just attractive, assuming the probability of fraud is zero; this occurs when the posterior $\widehat{\mu}_h(0)$ satisfies $\widehat{\mu}_h(0) = \mu_1(m)$. This condition does not depend on the cost of fraud, and so the boundary of the *No-Trust* regime is unaffected by the form of the cost of fraud.

Similarly, in the *Fund-Everything* regime, $\kappa_h = \kappa_\ell = 1$, so again there is no incentive to commit fraud. The boundary between this regime and the *Optimistic* regime is determined by the condition $\widehat{\mu}_\ell(0) = \mu_3(m)$. Again, this condition does not depend on the cost of fraud, and so this boundary is unaffected by the form of the cost of fraud. Furthermore, the condition $\delta C > \varepsilon + (\beta + \delta)\omega P$ guarantees that it is feasible to have a *Trust-Signals* regime, and then arguments along the lines just given prove that the boundaries of the *Skeptical*, *Trust-Signals*, and *Optimistic* regimes will be as in Proposition 3. Nevertheless, in the *Skeptical* and *Optimistic* regimes the probabilities with which investors provide unmonitored finance will be affected by the form of the cost of fraud, since the probability $\alpha$ of detecting fraud depends on these probabilities.[6]

If monitoring costs are low enough to permit monitoring ($m < \overline{m}$), matters are slightly more complex. Now, the fact that investors who monitor always catch fraud may shift the lower boundary of the region where fraud occurs with some probability. To see why, note that if investors always monitored all firms in the *No-Trust* regime, then a manager who committed fraud would be caught for certain and thus face cost $\varepsilon + P$. This may exceed the maximum benefit of fraud, which is $\delta C$. In this case, investors might actually be able to scale back monitoring, providing high-signal firms with unmonitored finance some of the time, without provoking fraud. Eventually, if the probability of unmonitored finance is high enough (and so the probability of monitored finance is low enough), some fraud will be attractive. The upshot is that part of the *Skeptical* regime may now be free of fraud. Indeed, if $P$ is high enough, even the *Trust-Signals* regime may be partially free of fraud, the reason being that monitoring of low-signal firms may be enough to deter fraud.

From this discussion, it follows that the main qualitative effect of having the cost of fraud reflect the probability of being caught (and, in particular, the probability of being monitored) is that when monitoring costs are sufficiently low, the region where fraud is possible may

[6] In particular, in the *Skeptical* regime, the probability $\kappa_h$ with which high-signal firms are given unmonitored finance will be higher than it would be if the cost of fraud $f$ was equal to $\varepsilon$ alone. In the *Optimistic* regime, the probability $\kappa_\ell$ with which high-signal firms are given unmonitored finance will be lower than it would be if the cost of fraud $f$ was equal to $\varepsilon$ alone. Essentially, the possibility of catching fraud raises the cost of fraud; this means that the benefit $\delta(\kappa_h - \kappa_\ell)C$ and thus the difference $\kappa_h - \kappa_\ell$ must be larger in order to get the manager to be indifferent between committing fraud and not committing fraud.

shrink further, with less fraud in regions with lower priors. This would reinforce the link between fraud and "good times."

## 6.3 Good Firms and Fraud

We have assumed that only managers of bad firms commit fraud. We now discuss how our results would be affected if managers of good firms could commit fraud. In a nutshell, there would be little change in our results in four of the five regimes – *Skeptical*, *Trust-Signals*, *Optimistic*, and *Fund-Everything* – but behavior in the *No-Trust* regime might be affected.

To see this, suppose that a good firm can commit fraud at cost $f'$, in which case its chance of producing a high signal goes from $\gamma$ to $\gamma + \delta'$, where $f' \geq f$ and $\delta' < \delta$. We assume that the cost of fraud is higher for good firms because, in a less stylized model, managers of good firms should have more to lose from being caught than managers of bad firms. For example, in a multiperiod setting, managers of good firms might find that being caught committing fraud ruins their chances of getting funding in the future – e.g., from SEC penalties. In that case, a good manager may be better off taking a higher chance of sending low signals now and not getting funding for current expansion, since she can return to the market the following period and try again. Similarly, we assume that fraud is more effective for bad firms because fraud should have a higher expected impact on bad firms' results than on good firms' results.

Now consider when a good firm would commit fraud. As for bad firms, the good firm's goal of fraud is to reduce the chance of being denied funding. If there is no investor monitoring ($m > \overline{m}$), committing fraud increases a good firm's chance of getting funding by $\delta'(\kappa_h - \kappa_\ell)$, as compared with $\delta(\kappa_h - \kappa_\ell)$ for bad firms. It follows that good firms have weaker incentives to commit fraud than do bad firms, and so the probability with which they commit fraud will be weakly lower than that with which bad firms commit fraud. All else equal, if good firms do commit fraud, the free signal actually becomes more informative, since a high signal is now more likely to come from a good firm. Since high signals are more attractive, this actually increases the incentives for bad firms to commit fraud. Nevertheless, the main thrust of our results would not be affected.

Suppose instead that investor monitoring is feasible ($m < \overline{m}$). In this case, the incentives for fraud differ qualitatively between good firms and bad firms. Bad firms wish to avoid being monitored, since this reveals them as bad; good firms do not mind being monitored, since this reveals them as good. It follows that in any regime where low-signal firms are monitored more frequently than high-signal firms, bad firms will have strictly more incentive to commit fraud than do good firms.

By contrast, if low-signal firms are monitored less frequently than high-signal firms, and firms are denied funding if they are not monitored, incentives reverse. (This corresponds to the sub-region marked "Monitor High Signals" in Figure 3, and its extension into the regions where fraud is possible.) Now, bad firms are not interested in committing fraud, because even a high signal cannot get them unmonitored funding, but good firms wish to be monitored so that they can prove their type. It follows that in this region, good firms may commit fraud with higher probability than bad firms.

Because this tends to occur for lower priors on the probability that firms are good, this runs counter to our main result that fraud is more prevalent for better priors. Nevertheless, this result must be taken with a grain of salt, since it requires that good firms who commit fraud are monitored and then not penalized by investors or the authorities for committing fraud. In practice, this seems unlikely. The act of committing fraud is not only a signal of incentives but a signal of a manager's ethics. In a less stylized model, finding out that a manager was willing to commit fraud in order to alter investor incentives is likely to be a bad signal for the future – after all, what will this manager be willing to do when the firm is truly in bad shape? If honesty is to be preferred in general, investors as well as the authorities may wish to replace a fraudulent manager now even if the underlying firm is good. In this case, good firms' incentives to commit fraud so as to be monitored disappear, and we are back to the situation analyzed in the base model.

To summarize this discussion, allowing good managers to commit fraud only has a major impact on our results when both monitoring costs and priors are relatively low, so that good firms may wish to commit fraud in order to boost their chances of being monitored. Nevertheless, this relies on the simplicity of our single-period model. In a model that incorporates multiple periods, investors and regulatory authorities are likely to wish to penalize fraudulent managers even if their firms prove to have good prospects. If this is the case, managers at good firms will have lower incentives to commit fraud even when priors are low, and the qualitative results of our base model continue to apply.

# 7 Conclusion

We have presented a simple model of incentives for firms to commit fraud in order to get funds from investors. Despite its simplicity, the model can motivate several patterns of behavior, such as changes in the prevalence of fraud over the business cycle and across different sectors and counterintuitive effects of changes in monitoring costs and investor priors. It also has some implications for policy on disclosure standards.

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# Appendix: Proofs

## A.1 Proof of Proposition 1

Investing without monitoring dominates not investing iff $V_U > V_N \iff \widehat{\mu}N_g - (1-\widehat{\mu})\,N_b > 0 \iff \widehat{\mu} > \frac{N_b}{N_b+N_g}$. Monitoring and investing in the good firm dominates not investing iff $V_M > V_N \iff \widehat{\mu}N_g - m > 0 \iff \widehat{\mu} > \frac{m}{N_g}$. Investing without monitoring dominates monitoring and investing in the good firm iff $V_U > V_M \iff \widehat{\mu}N_g - (1-\widehat{\mu})\,N_b > \widehat{\mu}N_g - m \iff \widehat{\mu} > 1 - \frac{m}{N_b}$. Threshold for $m$: monitoring is dominated if $\widehat{\mu} \leq \frac{m}{N_g}$ and $\widehat{\mu} \geq 1 - \frac{m}{N_b}$; combine $\widehat{\mu} = \frac{m}{N_g}$ and $\widehat{\mu} = 1 - \frac{m}{N_b}$, which yields $1 - \frac{m}{N_b} = \frac{m}{N_g}$, and the definition of $\overline{m}$. ■

## A.2 Proof of Proposition 2

The cut-offs for the five regimes can equivalently be defined using cut-offs for the posterior beliefs. Recall from (2) that

$$\widehat{\mu}_\ell\,(0) < \widehat{\mu}_\ell\,(1) < \widehat{\mu}_h\,(1) < \widehat{\mu}_h\,(0)\,.$$

These four cut-offs in the interval $[0,1]$ define the five regimes, depending on the location of $\mu_3\,(m)$ in relation to the four cut-offs (for example, the *Fund-Everything* regime has $\widehat{\mu}_\ell\,(0) > \mu_3\,(m)$).

- The proofs for the *Fund-Everything* and *No-Trust* regimes are straightforward.
- The *Optimistic* regime: $\phi \in (0,1]$ such that $\mu_3\,(m) < \widehat{\mu}_\ell\,(\phi)$ cannot be an equilibrium. If it was, $\ell$ signals would not be monitored, so there would be no benefit from committing fraud, i.e. $\phi = 0$. Similarly, $\phi \in [0,1)$ such that $\mu_3\,(m) > \widehat{\mu}_\ell\,(\phi)$ cannot be an equilibrium. If it was, $\ell$ signals would be either monitored or rejected, while $h$ signals receive unmonitored financing; so there would be an incentive to increase $\phi$. So in equilibrium, the bad firm chooses $\phi \in (0,1)$ such that with a signal $\ell$,

$$V_U = V_M \iff \widehat{\mu}_\ell\,(\phi) = \mu_3\,(m) \iff \phi = \frac{1}{\delta}\left(1 - \beta - (1-\gamma)\,\frac{\mu}{1-\mu}\,\frac{m}{N_b - m}\right). \quad \text{(A1)}$$

Next, $\kappa_h < 1$ cannot be an equilibrium, since $\mu_3(m) < \widehat{\mu}_h(\phi)\ \forall\phi$. Therefore, $\kappa_h = 1$ and $\lambda_h = 0$.

$\kappa_\ell = 1$ cannot be an equilibrium. If it was, there would be no incentive for bad firms to commit fraud, and therefore firms with a signal $\ell$ should not receive unmonitored financing. Similarly, $\kappa_\ell + \lambda_\ell < 1$ cannot be an equilibrium. If it was, $\ell$ signals would be rejected with positive probability. But that is not optimal for the investor since $\widehat{\mu}_\ell(\phi) = \mu_3 > \mu_1$, i.e. she strictly prefers monitoring an $\ell$ signal to rejecting it. Next, $\lambda_\ell = 1$, $\kappa_\ell = 0$ cannot be an equilibrium. If it was, bad firms would commit fraud with certainty. So in equilibrium, the investor chooses $\lambda_\ell$ and $\kappa_\ell$ such that $\lambda_\ell \in (0,1)$, $\lambda_\ell + \kappa_\ell = 1$, and

$$(\beta+\delta)\,C + (1-\beta-\delta)\,\kappa_\ell C - f = \beta C + (1-\beta)\,\kappa_\ell C \iff \kappa_\ell = 1 - \frac{f}{\delta C}.$$

- The *Trust-Signals* regime: $\widehat{\mu}_\ell(0) < \widehat{\mu}_\ell(1) < \mu_3(m) < \widehat{\mu}_h(1) < \widehat{\mu}_h(0)$, so $\ell$ signals are rejected or monitored while $h$ signals are financed without monitoring. By assumption, $\delta C > f$, so it pays for a bad firm to increase $\phi$ up to one. Signals $\ell$ are monitored iff

$$\widehat{\mu}_\ell(1) \geq \mu_1(m) \iff \frac{\mu}{\mu + (1-\mu)\,\frac{1-\beta-\delta}{1-\gamma}} \geq \frac{m}{N_g} \iff \mu \geq \frac{\frac{m}{N_g}\frac{1-\beta-\delta}{1-\gamma}}{1 + \frac{\gamma-\beta-\delta}{1-\gamma}\frac{m}{N_g}}.$$

- The *Skeptical* regime: $\phi \in (0,1]$ such that $\mu_3(m) > \widehat{\mu}_h(\phi)$ cannot be an equilibrium. If it was, all firms would be either monitored or rejected, and there would be no benefit from committing fraud. Similarly, $\phi \in [0,1)$ such that $\mu_3(m) < \widehat{\mu}_h(\phi)$ cannot be an equilibrium. If it was, $h$ signals would receive unmonitored financing, while $\ell$ signals would be either monitored or rejected, giving bad firms an incentive to increase $\phi$. So in equilibrium, the bad firm chooses $\phi$ such that with a signal $h$,

$$V_U = V_M \iff \widehat{\mu}_h(\phi) = \mu_3(m) \iff \phi = \frac{1}{\delta}\left(\frac{\mu}{1-\mu}\frac{m}{N_b - m}\gamma - \beta\right). \tag{A2}$$

If $\phi$ is such that $\widehat{\mu}_h(\phi) = \mu_3(m)$, the investor is indifferent between monitored and unmonitored finance for $h$ signals, and she prefers either option to rejecting an $h$ signal;

therefore $\lambda_h + \kappa_h = 1$. The investor mixes between monitored and unmonitored finance for $h$ signals, such that a bad firm is indifferent between committing fraud and not:

$$(\beta + \delta)\, \kappa_h C - f = \beta C \kappa_h \iff \kappa_h = \frac{f}{\delta C}.$$

So $\lambda_h = 1 - \kappa_h = 1 - \frac{f}{\delta C}$. Finally, $\kappa_\ell > 0$ cannot be an equilibrium. If it was, then $\widehat{\mu}_\ell\,(\phi) \geq \mu_3\,(m) = \widehat{\mu}_h\,(\phi)$, contradiction. So bad firms with an $\ell$ signal cannot expect to get financing at all. In equilibrium, $\ell$ signals are monitored iff

$$\widehat{\mu}_\ell\,(\phi) \geq \mu_1\,(m) \iff \mu \geq \frac{\frac{m}{N_g}}{1 - \gamma\left(1 - \frac{N_b}{N_g}\frac{m}{N_b - m}\right)}.$$

(and rejected otherwise). ■

## A.3 Proof of Proposition 3

- The proofs for the *Fund-Everything*, *Trust-Signals* and *No-Trust* regimes are straightforward.

- The *Optimistic* regime: $\kappa_h = 1$ since $\mu_2 < \widehat{\mu}_h\,(1) < \widehat{\mu}_h\,(0)$. Next, $\phi = 0$ can not be an equilibrium. The investor would not finance with a signal $\ell$, since $\widehat{\mu}_\ell\,(0) < \mu_2$. But then a bad would firm prefer to increase $\phi_2$ above zero, since $\delta C > f$. Similarly, $\phi = 1$ can not be an equilibrium. The investor would finance with any signal, so there would be no need to invest $f$. Next, $\kappa_\ell = 0$ cannot be an equilibrium. All bad firms would commit fraud with certainty, and the investor should then provide unmonitored finance for either signal, since $\mu_2 < \widehat{\mu}_\ell\,(1)$. Finally, $\kappa_\ell = 1$ cannot be an equilibrium. Bad firms would not commit fraud, and the investor should then reject $\ell$ signals, since $\widehat{\mu}_\ell\,(0) < \mu_2$. So the equilibrium must be in mixed strategies for both players. The bad firm chooses $\phi$ such that with a signal $\ell$,

$$V_U = V_N \iff \widehat{\mu}_\ell\,(\phi)\, N_g - (1 - \widehat{\mu}_\ell\,(\phi))\, N_b = 0 \iff \phi = \frac{1}{\delta}\left(1 - \beta - (1 - \gamma)\,\frac{\mu}{1 - \mu}\frac{N_g}{N_b}\right).$$

The investor chooses $\kappa_\ell$ such that

$$(\beta+\delta)\,C+(1-\beta-\delta)\,\kappa_\ell C-f=\beta C+(1-\beta)\,\kappa_\ell C \iff \kappa_\ell=1-\frac{f}{\delta C}.$$

- The *Skeptical* regime: $\phi=0$ can not be an equilibrium. The investor would not finance with a signal $\ell$, since $\widehat{\mu}_\ell(0)<\mu_2$. But then a bad would firm prefer to increase $\phi_2$ above zero, since $\delta C>f$. Similarly, $\phi=1$ can not be an equilibrium. If it was, the investor would not finance any firm, so there would be no need to commit fraud. Next, $\kappa_h=0$ cannot be an equilibrium. No firm would be financed, and therefore bad firms would not commit fraud; but then the investor should finance all $h$ signals, since $\mu_2<\widehat{\mu}_h(0)$. Finally, $\kappa_h=1$ cannot be an equilibrium. Bad firms would have an incentive to commit fraud with probability 1; but then the investor should reject all signals, since $\widehat{\mu}_h(1)<\mu_2$. So the equilibrium must be in mixed strategies for both players. The bad firm chooses $\phi$ such that with a signal $h$,

$$V_U=V_N \iff \widehat{\mu}_h(\phi)\,N_g-(1-\widehat{\mu}_h(\phi))\,N_b=0 \iff \phi=\frac{1}{\delta}\left(\frac{\mu\gamma}{1-\mu}\frac{N_g}{N_b}-\beta\right).$$

The investor chooses $\kappa_\ell$ such that

$$(\beta+\delta)\,\kappa_h C-f=\beta\kappa_h C \iff \kappa_h=\frac{f}{\delta C}. \qquad \blacksquare$$

## A.4 Proof of Proposition 4

The conditional probabilities are derived in Proposition 2. The ex-ante probability of fraud is calculated as $(1-\mu)\,\phi$ in each regime. ■

## A.5 Proof of Proposition 5

Follows immediately from (A2). ■

## A.6 Proof of Proposition 6

Follows immediately from (A1). ■